DOI:
10.1016/j.bspc.2018.05.036

Effect of Threshold Values on the Combination of EMG Time Domain Features: Surface versus Intramuscular EMG

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ABSTRACT

In myoelectric control, the calculation of a number of time domain features uses a threshold. However there is no consensus on the choice of the optimal threshold values. In this study, we investigate the effect of threshold selection on the classification for prosthetic use. Surface and intramuscular EMG were recorded concurrently from four forearm muscles on nine able-bodied subjects. Subjects were prompted to elicit comfortable and sustainable contractions corresponding to eight classes of motion. Four repetitions of three seconds were collected for each motion during medium level steady state contractions. The threshold for each feature was computed as a factor (R = 0:0.02:6) times the average root mean square of the baseline. For each threshold value, classification error was quantified using linear discriminant analysis (LDA) and k-nearest neighbor (KNN, k = 4) first for each individual feature and when combined. Three-way ANOVA revealed no significant difference between surface and intramuscular EMG ($P = 0.997$). However there was a significant difference between the features ($P = 0.006$) and between the classifiers ($P < 0.001$). The most dominant feature combination depended on the EMG (surface and intramuscular) and classifier. Results have demonstrated that using appropriate threshold value is very important to assure acceptable performance. For surface EMG, zero crossings (ZC) and slope sign changes (SSC) require no threshold, while a low threshold (R = 0.1:1) different from zero must be applied for willison amplitude (WAMP), myopulse percentage rate (MYOP) and cardinality (CARD). For intramuscular EMG, there is similar observation when using LDA as classifier. When using KNN, ZC SSC showed tendency to benefit from a low value threshold as well. Furthermore we propose the inclusion of a threshold that makes CARD robust to data precision.

Keywords: Electromyography; Pattern recognition; Time domain features; subject based optimum threshold; population based optimum threshold

I. INTRODUCTION

The electromyography (EMG) signal is one of the electrophysiological signals representing the neuromuscular activity during movements. It provides useful information about muscle condition. EMG based pattern recognition system have been extensively used in applications such as multifunctional upper limb prostheses [1-2], powered exoskeletons [3-4], rehabilitation robots [5-6], assistive computers [6-7] and wearable devices. Additionally, researchers and clinicians use profiles created by EMG features to investigate and diagnose neuromuscular conditions. Various pattern recognition algorithms have been proposed in the literature for the detection of motion intent [8-10]. Pattern recognition based control schemes extracts a set of features (time domain, frequency domain and time-frequency domain) that characterize the EMG signals in order to classify the user intended motions.

Multiple studies have evaluated the ability of various EMG features and classifiers to recognize different motions [10-12]. Classification accuracies > 90 percent have been reported in the literature [13-14]. Comparison of accuracies in these studies demonstrated that choice of features has more significant impact on the classification performance than the choice of classifiers [15-16,9]. Time domain (TD) features have been widely used in myoelectric control due to their computational simplicity and because they are easy to implement and do not require any signal transformation. Hudgins et al. (1993) introduced four TD features and now mostly referred to as Hudgins TD feature set [17]. Combining more robust and stable time domain features can significantly improve classification performance without increasing computation complexity [18].

Hudgins' set comprises the mean absolute value (MAV), waveform length (WL), slope sign change (SSC) and zero crossings (ZC). Among many other features that have been proposed, willison amplitude (WAMP) and myopulse percentage rate (MYOP) [19] have shown to contribute significantly to classification [10,20]. Recently Cardinality (CARD) has been proposed as a suitable feature [21] with improved performance. Features such as ZC, SSC, WAMP and MYOP are typically computed with a threshold value to attenuate the effect of background noise [18]. CARD feature does not require a threshold value, however, according to

[21], attention must be paid to the unit length (precision) used for signal processing prior to the computation of cardinality. Altering the dimension of the unit used for sampling (ADC resolution) to a high precision unit (for example a double) would alienate the discrimination power of cardinality. This is because every sample value would be unique so that cardinality will always be equal to the number of samples in the time window [21]. We acknowledge the value of this comment and we introduce a threshold value that should eliminate dependency of this feature on unit length. Meaning a sample is considered unique if and only if its distance to the previous sample (after sorting) is greater than the defined threshold.

Although several studies have investigated proper selection of representative features, very few have investigated the effect of optimum thresholds on classification accuracies. Variable threshold values have been reported in the literature and in most of the studies threshold values were ignored or arbitrarily fixed. Hudgins et al. (1993) used threshold value of 2 μV for computing ZC and SSC for decoding hand motions [13]. Phinyomark et al. (2008) used threshold values between 0.5 and 50 mV for WAMP [15], and showed that 5mV threshold performed best. Furthermore they extended the work by quantifying optimum threshold values for ZC and WAMP and concluded that thresholds are gain and instrument specific [22].

Recently [23] extensively studied the effect of threshold selection for ZC and SSC on the feature space and classification accuracy. Threshold for each feature was computed as a factor (R= 0:0.01:4) times the average root mean square of the data during rest period. Results demonstrated that threshold value has strong impact on features space and an optimum threshold value for each feature could be quantified, though with limited generalization ability. Nevertheless, the investigation was limited to surface EMG with two features and using only one classifier. Thus it is not known whether intramuscular EMG, which is gaining importance in myoelectric control, require different threshold levels compared to surface EMG.

In this study seven features MAV, WL, ZC, SSC, WAMP, CARD, MYOP features were investigated individually and in combinations to quantify the effect of each feature on classification error when the threshold is optimized for either surface or intramuscular EMG using Linear discriminant analysis (LDA) and *k*-nearest neighbor (KNN).

II. MATERIALS AND METHODS

A. Features

For this investigation, the focus is on the TD features which computation may require selection of a threshold value such WAMP, CARD, MYOP and we consider ZC and SSC for completeness. Table 1 summarizes all the features.

Table 1. Description of all features used in this study. N represents the total number of samples in a signal window; n is the sample index and ϵ is the threshold values defined in Equation (1).

Feature	Description	Formula
MAV	Mean Absolute Value (MAV) is the average of the absolute value of the EMG signal. It is an indication of muscle contraction levels.	$MAV = \frac{1}{N}\sum_{n=1}^{N}\lvert x_n \rvert$
WL	Waveform length (WL) is related to the fluctuations of a signal when the muscle is active. Thus, the feature provides combined information about the frequency, duration, and waveform amplitude of the EMG signal.	$WL = \sum_{n=1}^{N-1}\lvert x_n - x_{n+1} \rvert$
ZC	Zero Crossing (ZC) measures the number of crosses by zero of the signal and is related to the frequency content of the signal. This feature provides an approximate estimation of frequency domain properties	$ZC = \sum_{k=1}^{N-1}[(x_n \cdot x_{n+1} < 0) \cap (\lvert x_n - x_{n+1} \rvert > \epsilon)]$
SSC	Slope Sign Changes (SSC) measures the number of times the sign changes in the slope of the signal. It is another method to represent the frequency information of sEMG signal.	$SSC = \sum_{n=2}^{N-1}[(x_n - x_{n-1}) \cdot (x_n - x_{n+1})] > \epsilon$
WAMP	Willison Amplitude (WAMP) estimates the number of active motor units, which is an indicator of the level of muscle contraction.	$WAMP = \sum_{n=1}^{N-1}\lvert x_n - x_{n+1} \rvert > \epsilon$
MYOP	Myopulse Percentage Rate (MYOP) is defined to be the average value of the myopulse output. The myopulse output	$MYOP = \frac{1}{N}\sum_{n=1}^{N}\lvert x_n \rvert > \epsilon$

	is defined as one when the absolute value of a signal is above a threshold and Zero otherwise.	
CARD	Cardinality of a set is a measure of the number of distinct values. This can be computed in two steps. Data needs to be sorted and one sample is distinct from the next if the difference is above a predefined threshold.	Step 1: $y_n = sort(x_n), n = 1{:}N$ Step 2: $CARD = \sum_{n=1}^{N-1} \lvert y_n - y_{n+1} \rvert > \epsilon$

As proposed by [23], threshold is defined as a factor (R) times the average (across channels) root mean square value of the EMG signal at rest (during no contraction) (Eq. 3). In this study R ranges from 0 to 6 with a step of 0.02.

$$\epsilon = R * \sqrt{\frac{1}{N}\sum_{j=1}^{N}(x_{NM}[j])^2} \tag{1}$$

where $x_{NM}[j]$ are the samples of the signal at rest, and N is the total number of samples and NM stands for no motion which the signal measured during rest.

B. Experimental procedures

For this investigation, we used data for both surface and intramuscular EMG. Experiments were conducted on nine able-bodied subjects (age range: 19 - 26 yrs). The procedures were in accordance with the Declaration of Helsinki and approved by the local ethic committee of Northern Jutland (approval no.: N-20080045). Subjects provided their written informed consent prior to the experimental procedures. Subjects had no history of upper extremity or other musculoskeletal disorders. Surface and intramuscular EMG data were recorded concurrently from the following muscles: flexor carpi radialis, flexor digitorum superficialis, extensor carpi radialis and extensor digitorum communis. The complete experimental setup is shown in Figure 1. Surface EMG was recorded using four bipolar electrodes (Ambu WhiteSensor 0415). Surface EMG signals were analog bandpass filtered between 10 – 500 Hz. Intramuscular EMG was recorded using a pair of wire electrodes. Intramuscular wire electrodes were made of Teflon-coated stainless steel (A-M Systems, Carlsborg WA, diameter 50 µm) and were inserted into each muscle with a sterile 25-gauge hypodermic needle. Intramuscular signals were analog bandpass filtered between 0.1 and 4.4 KHz. All signals (surface and intramuscular) were amplified (AnEMG12, OTbioelletronica, Torino, Italy), A/D converted using 16 bits (NI-DAQ USB-6259), and sampled at 10 kHz. Subjects were prompted to elicit comfortable and sustainable contractions corresponding to eight classes of motion; wrist flexion, wrist extension, hand close, hand open, key grip, pinch grip, chuck grip and no motion. Four repetitions of three seconds were collected for each motion, during which the unconstrained subjects held a medium level contraction to capture signals at steady state. A reference electrode was placed close to the carpus.

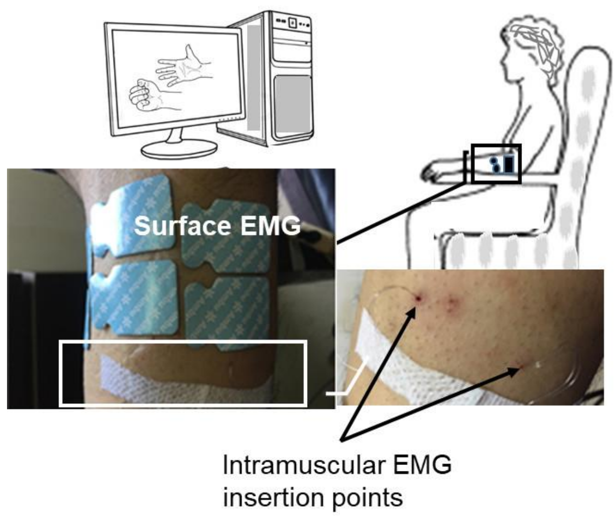

Figure 1: Experimental setup with the subject comfortably sitting in front of a computer that visualizes the motions to be elicited. The photographs are actual placement of the electrodes and insertion points.

C. *Data analysis*

Seven time-domain features were extracted from incrementing (by 25 ms) analysis windows of 250 ms in duration for each value of *R*. On average, only one millisecond was needed for the classification of a single segment. We carried data analysis in the following steps:

1. Single feature investigation with the purpose of quantifying the effect of threshold on single feature based classification.

2. Combination of each threshold-based feature with mean absolute value (MAV), using subject based optimum threshold (SBOT) and population based optimum threshold (PBOT).
3. Investigation of all possible feature combinations in order to study how optimum threshold affects the best combination of features.

Classification Error (CE) was quantified using four-fold validation procedure with Linear Discriminant Analysis and *k*-nearest neighbour ($k = 4$) as classifiers. CE was computed as the number of samples incorrectly classified (false positives plus false negatives) divided by the total number of sample cases. Linear Discriminant Analysis (LDA) is a classification method originally developed in 1936 by R. A. Fisher [24]. It is simple, mathematically robust and often produces models whose accuracy is as good as more complex methods. The *k*-nearest neighbour (kNN) rule, first introduced by Fix and Hodges (1951), is one of the most straightforward nonparametric techniques [25]. The basic principle behind the kNN rule is that the most likely assignment for a queried pattern is the class most often represented by its bordering exemplars.

D. Statistics

Three-way repeated measure analysis of variance (ANOVA) with factors classifiers, EMG modalities and features was used to compare CE using optimum threshold. P-values less than 0.05 were considered significant. The Bonferroni–Dunn adjustment was used for multiple comparisons. Results are given as mean ± standard deviation.

III. RESULTS

A. Single feature investigation

Three-way ANOVA revealed no significant difference between CE obtained from surface and intramuscular EMG (P = 0.997). There was a significant difference between the features (P = 0.006), with SSC (0.21 ± 0.078) performing significantly worse than WAMP (0.153 ± 0.063) and CARD (0.161 ± 0.066). Furthermore MAV (0.186 ± 0.072) performed worse than CARD. There was also a significant difference (P

< 0.001) between the classifiers with KNN (0.154 ± 0.063) performing better than LDA (0.201 ± 0.066). A significant interaction was found between EMG and classifiers (P = 0.047) and between classifiers and features (P = 0.043), suggesting that performance of both the classifiers and the features depend on the type of EMG signal as depicted in Figure 2. For example, SSC has a lower error value using intramuscular than with surface EMG.

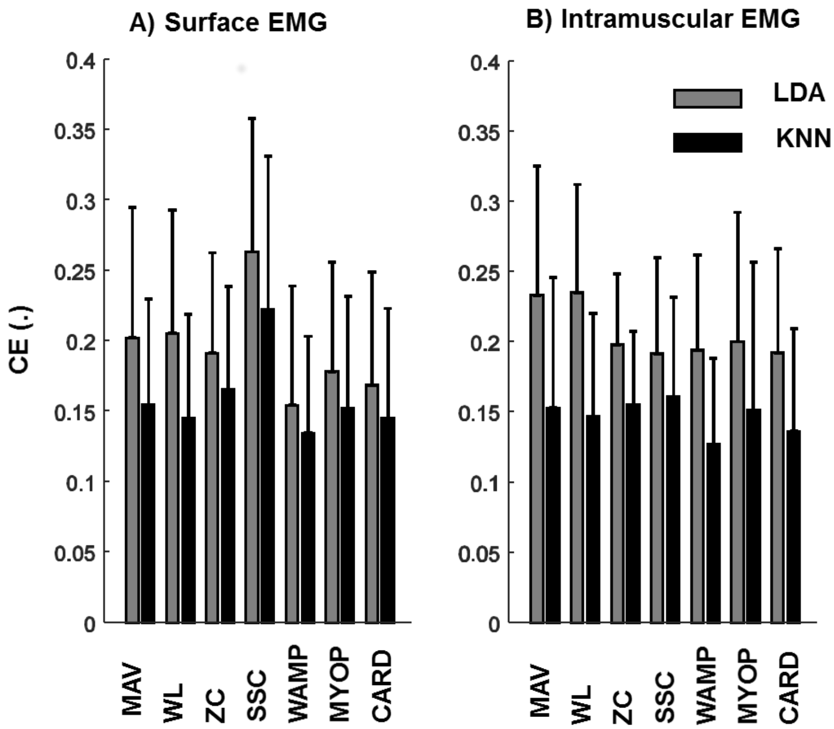

Figure 2: Classification error (CE) for A) surface and B) intramuscular EMG using single classification features at different *R* value.

B. Adding MAV to each single features

In the second stage, we investigated performance using two features. Figure 3 depicts the effect of increasing threshold on the performance using the combination of MAV with each single feature. The general view of Figure 3 indicates that the performance of all features is threshold dependent. For surface EMG, ZC and SCC requires no threshold, while a low value threshold different from zero must be applied for WAMP, MYOP and CARD features. For intramuscular EMG, there is similar observation when using LDA as classifier. When using KNN, ZC and SSC may benefit from a low value threshold as well.

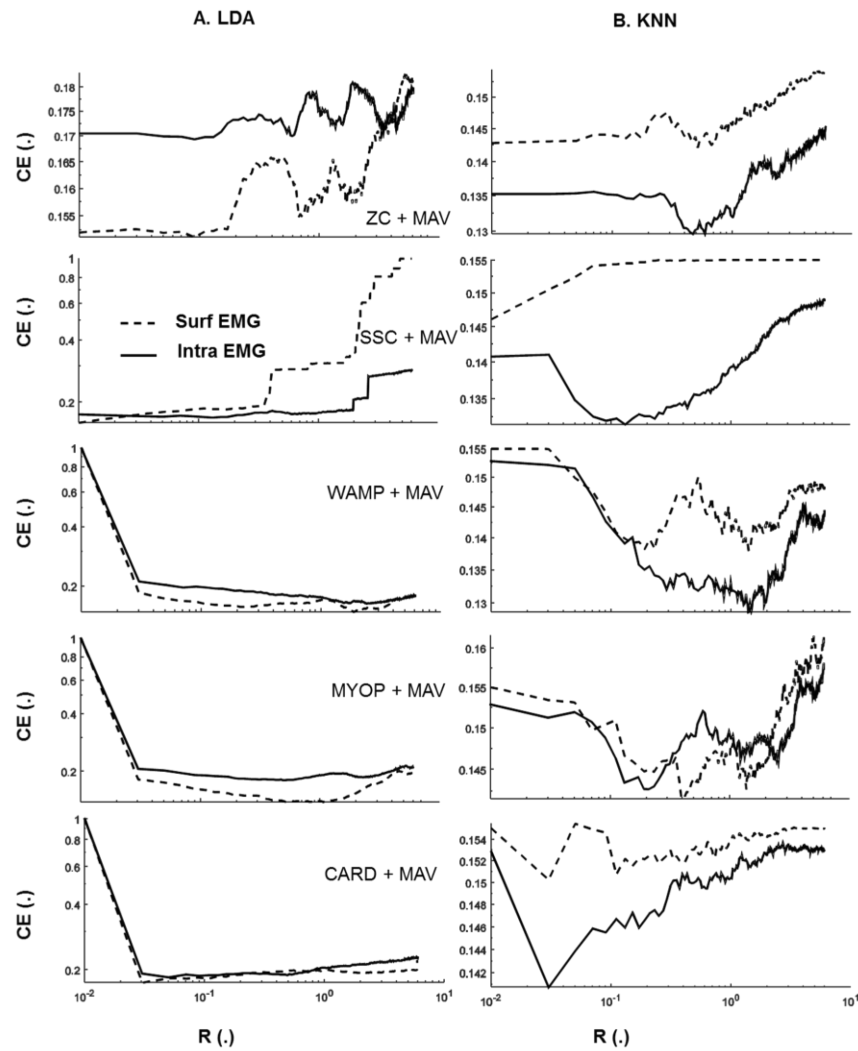

Figure 3: Result obtained for each feature combined with mean absolute value (MAV) for surface (dashed line) and intramuscular (plain line) EMG using A) linear discriminant analysis (LDA) and k-nearest neighbor (KNN). Each subfigure represents the classification error computed at different threshold levels. Both axes are logarithmic for clarity.

Figures 4 and 5 depict the performance of using dual features with SBOT and PBOT for surface and intramuscular EMG respectively. Using surface EMG, the ensemble average was 0.133 ± 0.063 using SBOT and 0.149 ± 0.066 using PBOT, significantly different ($P < 0.001$). No difference was found between LDA and KNN ($P = 0.236$) but a difference was found between features ($P = 0.037$). When using intramuscular EMG, we found a significant difference ($P < 0.001$) between SBOT (0.138 ± 0.072) and PBOT (0.154 ±

0.075). There was a significant difference (P = 0.045) between KNN (0.128 ± 0.072) and LDA (0.168 ± 0.081). Lastly there was no difference between features (P = 0.290).

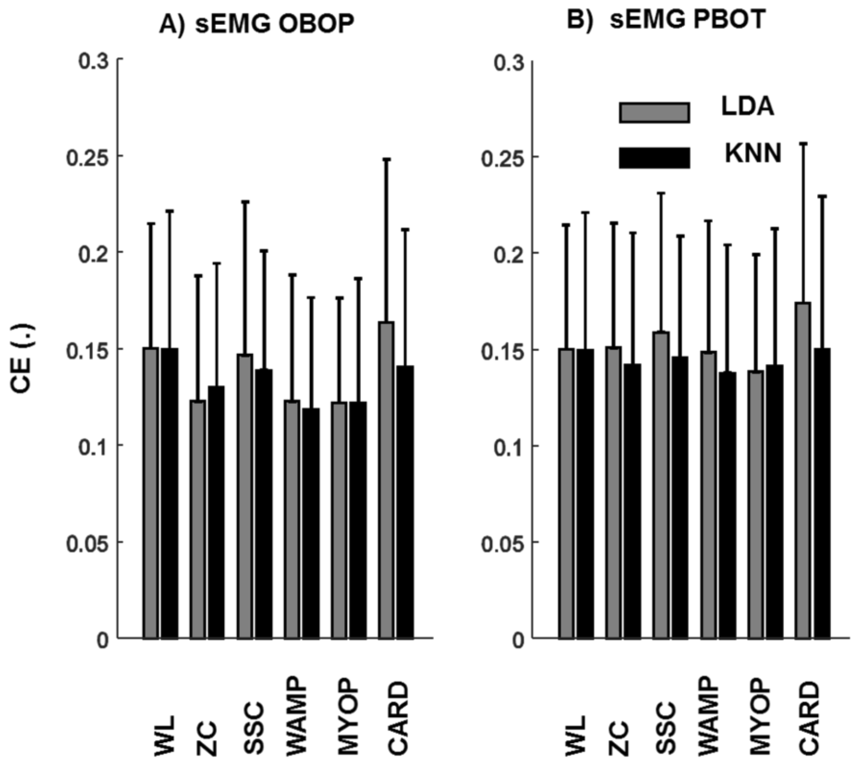

Figure 4: Classification error (CE) of surface EMG (sEMG) for each feature used in combination with Mean absolute value (MAV) at different *R* values optimized A) on subject based optimum threshold (SBOT) and B) on population based optimum threshold (PBOT).

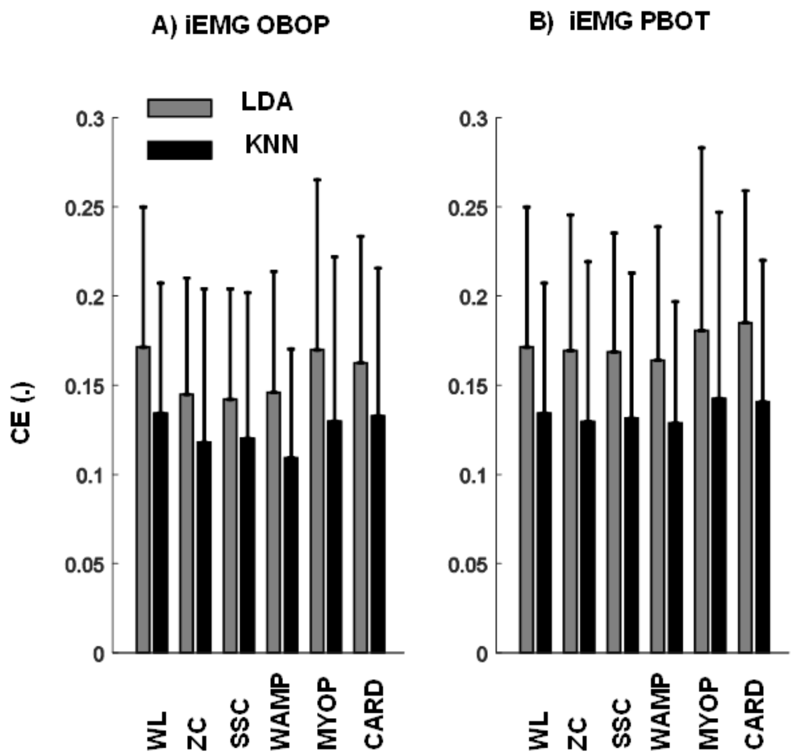

Figure 5: Classification error (CE) of intramuscular EMG (iEMG) for each feature used in combination with Mean absolute value (MAV) at different *R* values optimized A) on subject based optimum threshold (SBOT) and B) on population based optimum threshold (PBOT).

This investigation showed that the best combination of features depends on the threshold value. Table 2 summarizes the best feature combination for each EMG type and classifier when using one to four features. It is clear that the most contributing features differ between surface and intramuscular EMG.

Table 2. Best combination of features based on EMG types and classifiers. For each classifier, the optimal error is provided and for each feature combination, the achieved error is provided for comparison.

	Surface EMG		**Intramuscular EMG**	
# of Features	LDA (8.82%)	KNN (10.4%)	LDA (9.23%)	KNN (8.63%)
1	WAMP (15.44%)	WAMP (13.47%)	SSC (19.16%)	WAMP (12.7%)
2	WAMP, MYOP (10.44%)	WAMP, MYOP (10.78%)	WL, SSC (13.78%)	WL, ZC (10.05%)

3	WL, ZC, MYOP (9.47%)	WAMP, MYOP, MAV (10.49%)	WL, ZC, SSC (11.42%)	WL, SSC, ZC (9.21%)
4	MYOP, CARD, MAV, ZC (9.32%)	WAMP, MYOP, MAV , ZC (10.46%)	WL, ZC, SSC, CARD (10.28%)	WL, ZC, SSC,CARD (8.79%)

Figure 6 provides an illustration of the performance per subject when using a single feature (best vs. worst). It is clear that choice of best feature is consistent across subjects.

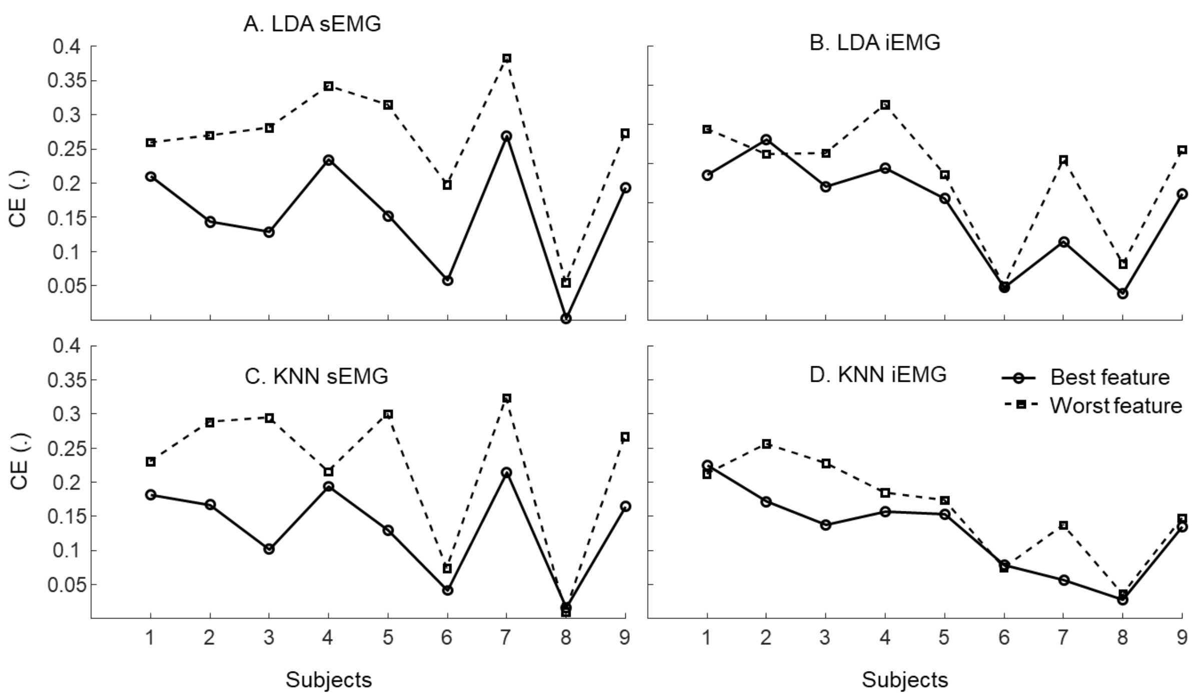

Figure 6: Single feature performance per subject with best and worst feature using A. Linear discriminant analysis (LDA) with surface EMG (sEMG), B. LDA with intramuscular EMG (iEMG), C. *k*-nearest neighbour (KNN) with sEMG and D. KNN with iEMG.

IV. Discussion

In the present study, we investigated how thresholding TD features (ZC, SSC, WAMP, MYOP and CARD) affects classification performance using LDA and KNN. The aim was to test whether these features will behave differently when applied to surface and intramuscular EMG. As in real case, surface and intramuscular can be combined for myoelectric control. An intramuscular electrode can acquire signals from small and deep muscles providing localized information and thereby greatly increasing the information to control a prosthetic device. Furthermore, we investigated how optimum threshold affects the combination of features. Using LDA, our investigation revealed that the performance of each feature (combined with MAV) with respect to threshold is similar between surface and intramuscular EMG. That is ZC and SSC does not require optimum threshold and performed well as long using R = 0 as also reported in our previous study using multi surface EMG datasets [Kamavuako et al. 2016]. However, the remaining features (WAMP, MYOP and CARD) must include a threshold in order to contribute to class separability. In fact, using R = 0, these features produce the same output reducing the classification performance significantly. In this study the required threshold value for these features were between 0.1 and 1 times the RMS of the baseline. Similar observation was made using KNN and surface EMG. Nevertheless, ZC and SSC may beneficiate from a small threshold value when applied to intramuscular EMG with KNN.

Previous studies have argued that MAV and WL contain most of the signal information for classification [Phinyomark et al. 2013]. The results of the present study do not support this statement as shown in Figure 1, as other features may contain more discriminative information compared to MAV when the threshold value is optimized per subject. Most of the previous studies did apply a fixed threshold, which may have been too high resulting in degradation of the discriminative power of the features. We observed that each subject had a unique global minimum, supporting the initial suggestion made by [Hudgins et al 1993] for reducing aberrant zero crossings or slope sign changes resulting from additive noise. Although we observed that performance based on PBOT was less than 2 % point from SBOT, recommendation is to use the range of threshold provided above instead of opmizing each time. Furthermore we have shown that introducing a threshold value in the computation of cardinality makes this feature independent of data precision and increases the discriminative power of the feature.

The second part of this study focused on combination of features. Figures 3 and 4 have revealed that combination of MAV and WL may be outperformed by other pair of features with proper threshold values.

When only one feature is needed, WAMP seems to show highest performance compared to others. In dual features, WAMP and MYOP of the surface EMG were the combination with the lowest error. In the case of intramuscular EMG, WL and SSC depicted highest peformance. Furthermore addition of ZC and CARD showed consistency for both classifiers with intramuscular EMG. WL and MAV have emerged in combining three and four features of the surface EMG with the MYOP being consistenly one the features. It should be noted that other combination may have exhibited slightly similar performance, but we only reported the combination with the lowest absolute value of the error.

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V. Conflict of Interest

The authors Asim Waris and Ernest Nlandu kamavuako declare that there is no conflict of interest regarding the publication of this article “Effect of Threshold Values on the Combination of EMG Time Domain Features: Surface versus Intramuscular EMG”.